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Predictive biometrics: a review and analysis of predicting personal characteristics from biometric data

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Abstract: Interest in the exploitation of soft biometrics information has continued to develop over the last decade or so. In comparison with traditional biometrics, which focuses principally on person identification, the idea of soft biometrics processing is to study the utilisation of more general information regarding a system user, which is not necessarily unique. There are increasing indications that this type of data will have great value in providing complementary information for user authentication. However, we have also seen a growing interest in broadening the predictive capabilities of biometric data, encompassing both easily definable characteristics such as subject age and, most recently, ”higher level” characteristics such as emotional or mental states. This paper will present a selective review of the predictive capabilities, in the widest sense, of biometric data processing, providing an analysis of the key issues still adequately to be addressed if this concept of *predictive biometrics* is to be fully exploited in the future.

1. Introduction

The field of biometrics is now established as a mature and important area where practical solutions to many real-world problems have been realised, and the influence of which is rapidly growing. There is a world-wide research base of impressive and diverse innovative work which is allowing the field to continue to expand and develop, and it is therefore a field with a growing and increasingly detailed literature.

The principal focus of biometrics has always been the identification/verification of individuals based on the measurement and analysis of personal physiological or behavioural characteristics, and this remains the target application for most of the current research reported. Indeed, various comprehensive reviews of this fundamental aspect of biometrics research can already be found [18, 22, 87, 132, 138, 141].

To take just one illustrative but more specific task area (of particular interest later in this paper), the studies reported in [49, 122, 148, 14, 65, 134, 113, 93, 61] present different approaches to user identification and authentication based on the analysis of keystroke dynamics. There are commercial systems available which include keystroke monitoring as part of a general security system. [137] reports a systematic review of keystroke dynamics for user recognition, while [122, 143, 160, 30, 80, 159] present solutions for using keystroke dynamics to enhance the password used in a typical access control environment. [168] introduces a novel capability to determine the operating environment (desktop/laptop) in use.

However, the biometrics field remains dynamic, and current efforts often seek to broaden both application areas (for example, progress towards robust and reliable mobile biometrics environments [9, 20, 106, 187]) and strategies to enable greater scope and convenience in adopting biometric solutions (for example, a trend towards effective techniques for "biometrics at a distance" [57, 75, 98, 140], where capture environments are less restricted than hitherto). More recently, there has been a significant increase in interest in exploring the interface between biometrics and forensic analysis and exploiting links between the two, and this is generating ideas and techniques of real benefit to both disciplines [24, 35, 83, 154, 155, 189].

Beyond this, other related topics in the general area of biometrics are of rapidly developing interest. For example, the notion of exploiting "soft biometrics" (biometric characteristics which are specific to an individual, but not in themselves unique - subject age, for example, or gender) is not new, but has gained in prominence, both as a means of supplementing unique biometric data to improve identification processes and as a way of determining additional information about individuals or particular application scenarios which may prove useful in specific contexts [8, 12, 16, 42, 69, 74, 88, 107, 128, 151, 177].

Of particular interest in this paper, however, is a somewhat different - although closely related - option. This relates to the ability to *predict* soft biometric characteristics from conventional biometric data. For example, an ability to determine the age or gender of a subject from a facial image, or the handedness of a writer from a sample of her signature, have obvious practical importance which suggests powerful and valuable application possibilities, not least at the biometrics-forensics interface noted above. Again, this is an area which has a relatively long history (particularly when the biometric modality of interest relates to facial characteristics - see, for example [164, 157]), but the work reported is generally much less extensive, and comprehensive review material of wide generality in this area is relatively hard to find.

The increasing research effort devoted to this area suggests that a more comprehensive review of the field and an analysis of its success and future development is timely, and this is expressly what this paper seeks to provide. However, our aim is only partly to draw together the variety of contributions to this topic from the published literature, and we want this review to extend beyond these narrow limits. For example, there has recently been a discernible move towards computing more generalised predictive individual characteristics from biometric data, and specifically indicators which are often referred to as "higher level" characteristics ([51, 52]), which can include such aspects as the "emotional state" of a subject. Here the literature is very much less extensive although, as noted above, the facial biometric modality provides the most common examples (for example, there is much work to be found on assessing facial expression, which is an indirect way of extracting information about these "higher level" states (see, for example, [39])). Our study will therefore extend to this area, making it, to our knowledge, the first review which provides such a comprehensive coverage of the topic.

In this paper, our aim is therefore to provide a broad-based review of the predictive capabilities of systems which acquire typical biometric data as their fundamental core function. The paper will first provide an overview, necessarily somewhat selective, of the current field as reported in the literature, and we will include an integrated study of both conventional prediction of soft biometric characteristics and the prediction of the higher level attributes noted above. We have termed the activities associated collectively with such processing "predictive biometrics", although, of course, conventional biometrics-based person identification is also a prediction task in a way. We will then provide a broad analysis of the current status of the field, summarise current capabilities and, importantly, explore some ways in which the field can most effectively be developed in the future.

2. Prediction from biometric data

There is a diverse, if somewhat limited, body of research reported in the literature on how to use soft biometric information to improve the performance of a traditional biometric system and also, looking in the opposite direction, on how to predict such information. However, the principal aim of this paper is to explore the more general predictive capabilities of this type of data.

We will divide our broad survey into two sub-sections, the first (Section 2.1) dealing with conventional prediction of demographic information typified by, but not restricted to, subject age or gender. We refer to these properties as *lower level* soft biometrics. The second (Section 2.2) deals with the prediction of what can be called the emotional or mental state of a subject, and we refer to these properties (for example, whether a subject is happy or sad, stressed or relaxed, and so on) as constituting *higher level* characteristics. It should be acknowledged that such characteristics are not "soft biometric characteristics" in the usual sense of the term, since they can change on a short timescale and will vary considerably among individuals at different times. Nevertheless, in the context of understanding predictive capabilities, and since they are of significant value in a variety of biometrics-based applications, we regard such properties as an extension of more conventional soft biometrics, although they generally cannot be considered as effective in contributing directly to the identification of an individual. As we have noted, there are also significantly fewer reported studies of the latter type than the former.

2.1. Prediction of lower level soft-biometric information

Even though the primary aim of biometric processing to date has been to establish or confirm individual identity, it is increasingly recognised that there is a close link between identification of individuals and situations commonly targeted by biometric systems where the prediction of important characteristics from that individual is also necessary [82, 135, 41].

Part of the analysis of biometric data might well therefore include the need to estimate a more general characteristic (such as age or gender, for example) of the "owner" of the specific piece of information under consideration. Predicting such characteristics of an individual has wider application, but the investigations reported in the following sub-section will focus on work related to the prediction of one or more types of demographic information.

2.1.1. Age estimation: In [54, 144], the authors present a survey of state-of-the-art techniques in the synthesis and estimation of facial images from the point of view of age characterisation. Existing models and algorithms, system performances, technical difficulties, popular face ageing databases, evaluation protocols, and promising future directions are also systematically discussed.

As expected, the large majority of age prediction studies concern the analysis of facial data. The main concerns of such studies can be grouped into three classes of investigation:

- Studies of different features for age estimation or the main features that are affected by ageing [59, 60, 84, 97, 103, 70, 133, 145, 153, 170, 175, 185, 129, 96, 29, 8, 186, 176, 34, 111, 181, 165]. Prediction accuracies reported range from 93% (whenusing facial ageing patterns) to 73% (when using Local Binary Pattern operators) although, as we note below, caution is needed in interpreting such comparisons.
- Studies regarding different algorithms which are able to deal with the differences in facial appearance caused by ageing effects [64, 66, 68, 71, 73, 92, 101, 127, 136, 28, 102, 190, 32, 11, 110, 109, 171, 58]. Prediction accuracies reported range from 83% (when using nearest

neighbour-based classification) to 70% (when using genetic algorithms).

- Studies which focus on dealing with the age-related changes in the face through the fusion of information or by using ensembles of classifiers [67, 89, 108, 188]. Prediction accuracies reported range from 95% (when using SVM as the fusion algorithm) to 92% (when using subspaces techniques).

Meaningful comparative analysis is extremely difficult because of the diversity of experimental conditions encountered in these studies, yet some broad discussion is useful. First, it is apparent that, despite the large number of papers, this specific strand of research is somewhat limited in the scope of its reported investigation. As an example, [59, 60] present very similar work regarding a new algorithm for age estimation using different databases. The same occurs in [66, 68, 71, 70].

It is very clear that the variety of different techniques used to identify features is somewhat limited. For example, the use of manifold-based and subspace-based structures is a common choice [97, 29, 32, 66, 109, 176, 181].

Regarding classification techniques, the use of probabilistic techniques such as Bayesian learning [101, 67, 175] is very popular. Another technique which is frequently encountered is the use of Support Vector Machines, following the trend that this technique has achieved within the wider biometrics community in more traditional applications [16, 40, 60, 110, 153].

There are relatively few databases available which provide the necessary demographic information for such analysis, as can be seen in Table 1 but, nevertheless, even a limited number of different datasets means that comparisons across databases should be interpreted with caution, since performance variations (such as those noted above) are clearly affected by the experimental parameters. It is important to note, for example, that different databases can adopt different age bands to characterise subject age distribution, rendering performance comparisons much less meaningful.

Table 1. *Largest databases available (as noted in the literature) that contain age information*

Ref.	Modality	Database	Qtt	Users	Age	Ethnicity
[60]	Face	FG-NET	1002	82	0 to 69	Asian
[23]	Face	MORPH	1724	515	15 to 68	Asian
[70]	Face	YGA	8000	1600	0 to 93	Asian
[172]	Face	PAL	540	540	18 to 93	Mixed
[127]	Face	Flickr	28231	5080	0 to 66	Mixed

Other biometric modalities have received rather less attention from the research community, but investigations can be found for age prediction using modalities such as the handwritten signature [45, 48]. The investigation of age prediction from gait data can be found in [107, 114], while [46, 151] investigate the prediction of age from iris data using different sets of geometric and texture features. In [128, 56, 40], the authors have investigated the prediction of age from voice data, and [120] examines the prediction of subject age from the fingerprint. Predictive accuracies range from a minimum of 57% (for the iris modality) to a maximum of 77% (for the signature modality), but the problems noted above make drawing specific conclusions unwise.

Finally, there is a very strong inclination in the literature to focus mainly on the use of facial features for age prediction. There appears to be much less interest in using behavioural modalities, such as handwritten signature, keystroke dynamics, or even speech analysis for this end, and there may be some value in broadening investigations to include such modalities.

2.1.2. Gender prediction: Once again, the majority of gender prediction papers concern the analysis of facial data (for example, see [26, 115, 118, 162, 163, 178, 177, 17]). The main focus of these studies is the use of PCA for object identification on the faces and Support Vector Machines for gender classification. As in the previous case, Table 2 shows that there are a limited number of databases available providing the data required to undertake this sort of study. Predictive accuracies reported range from 91% (when using Bayesian algorithms with the Face modality) to 95% (when using SVM with keystroke dynamics). Many of the same difficulties of producing a comparative analysis of these studies as noted in the previous section apply also in this case, although assigning a gender category to subjects is less of a problem than with age, where specific age is generally subsumed within a set of more general age bands.

Table 2. *Largest databases reported in the literature for gender analysis*

Ref.	Modality	Database	Males	Females	Ethnicity
[25]	Face	CAESAR	1119	1250	Mixed
[26]	Face	MUCT	131	145	Mixed
[147]	Face	XM2VTS	160	135	Mixed
[38]	Keystroke and Signature	Hand-based Brazilian	31	88	Mixed

Much less work is reported regarding gender prediction from other modalities. A study which explores gender prediction from keystroke dynamics is reported in [49], two studies can be found which deal with the prediction of this characteristic using iris data [158, 161]. Naturally, the passage of times brings opportunities to explore new and different modalities. The analysis of EEG and ECG signals are an example of such a modality, especially when considering conventional biometric identification tasks, but so far less so for more general prediction tasks. However one study can be found of gender prediction from EEG [131].

Again, we can see a similarity with the age prediction situation here. Studies of gender prediction are less widespread than for age prediction but face can again be seen as the most adopted modality for such investigations. As with age prediction, there are also fewer studies using behavioural modalities, such as handwritten signature or keystroke dynamics, and this may suggest some potentially fruitful future studies.

2.1.3. Multi-soft-biometric prediction: A number of reported studies can be found which predict gender or age together with other soft-biometrics data. These papers also implicitly summarise reported work on the prediction of other soft biometric characteristics which are less commonly considered generally. Examples include the prediction of:

- Age and Gender from voice [12, 121].
- Age and Gender from face [16, 88, 42].
- Age and Gender from gait [191].
- Age and Height from gait [31].
- Gender and Ethnicity from iris [91].
- Age, Gender and Ethnicity from face [164, 69, 74].
- Gender, Handedness and Age from writing [21].

- Gender and Height from gait [142, 25].
- Gender and Age from EEG [126].

It is clear from the list already shown that a significant interest in multi-soft-biometric prediction is relatively recent and, therefore, it is possible to find a varied group of demographic indicators being predicted in each modality, not necessarily with a specific focus on any group.

The prediction of multiple characteristics from a single data source has not produced any noteworthy advances in performance, although clearly this is an approach which has positive practical implications. It is possible that a useful alternative would be to explore further the possibility of predicting individual soft biometric characteristics from multiple biometric sources although, as will be seen later, this raises important issues about database planning and availability.

2.2. Prediction of higher level individual characteristics

We have made it clear that a principal (and particularly novel) strand of this paper is to consider the question of predicting so-called ”higher level” characteristics from biometric data. Various biometric modalities have been used in a range of studies which deal with the analysis of such states although, for obvious reasons, these are principally behavioural modalities. These higher level predictions might typically relate to conditions broadly describable as ”mental” or ”emotional” state in varying forms (here we will use the terms interchangeably, although we recognise that individual studies may adopt stricter and more formal definitions). Thus we can also consider the possibility of extending and developing the predictive capability of biometric measurements to these higher level states, exemplified by characteristics such as how happy or sad, or how calm or stressed an individual is feeling. A knowledge of, for example, the state of mind of an individual as happy or sad, anxious or calm, under stress or relaxed, and so on, might provide information which could be extremely valuable in interpreting particular scenarios or evaluating human activities in a variety of situations.

In order to determine accurately a person's mental/emotional state, it is helpful to look at the work reported in [37], where the author presents a survey of ground-truth labelling in emotion-dependent data and raises some important questions, such as whether any incongruity exists between perceived and experienced emotion which might lead to doubtful annotations. Issues such as this lead the author to address factors such as the following: choice of participants (age, social and cultural groups), choice of emotion model (discrete emotion model or dimensional model), choice of induction context, modalities and annotation strategies.

Contributions found in [105, 72, 77] discuss the influence that music audio can have on mental state and how it can function as an induction method, while [27] represents a discrete approach to emotion assessment. Although reported studies concerning these higher level attributes are less widespread than the prediction of the more traditional lower level attributes, they nevertheless provide a very important foundation to the understanding of predicting emotions. However, the prediction of higher level states has been reported for a number of biometric modalities, such as the following:

- Keystroke dynamics: Typing activity is one of the main ways in which individuals interact with a computer, and has become a significant part of people's daily routine behaviour. There are a number of studies which use keystroke dynamics to determine mental state and, in particular, human emotions. For example, [192] measures mood based on monitoring mouse and keyboard activity, while [6] presents a system basing its inference about emotions on student data captured from keyboard and microphone. [78] presents a novel approach to recognising emotion in software engineering, and [174, 78, 43] focus on detecting stress from keystroke interaction, while [149] asks the participants to perform several mathematical exercises while data is captured from the keyboard and used to detect emotion. [90] provides a review of emotion detection based on keystroke and movement, [19] focuses on detecting boredom and engagement during typing, and [169] offers a different perspective by combining facial feedback with keystroke for emotion prediction. [13] combines keystroke, mouse and touch-screen interactions to detect human emotions, and [52] exploits the application of emotion prediction in healthcare scenarios.

- Many studies can be found which investigate the analysis of handwriting and drawing movements in healthy subjects (exemplified by [119], for example), but handwriting has also been shown to be a good indicator of a writer's mental state [125, 63, 139, 77].

- Face: Again, this is one of the most studied modalities for emotion recognition, although here it is actually the computation of *facial expression* which is the principal determinant of recognising an individual's emotional state. In [5], the authors note that recognising facial emotional characteristics draws on "multiple strategies" and the study demonstrates that "emotion recognition is not monolithic but consists of a diverse array of strategies and processes". [99] takes on the challenge of determining facial expressions with a "single-image-based" face recognition system and the proposed method achieves 77.3%-84.0% recognition rate with a KNN classifier, while [167] introduces an additional modality (keystroke information) to improve the accuracy of emotion recognition. The authors present a result which suggests that two modalities can achieve different recognition accuracies depending on the emotion in question, and that they can complement each other. [184] presents a more effective approach using an adaptive discriminative metric instead of the more conventional simple Euclidean distance metric when recognising facial expressions, in order to increase the effectiveness of characterising similarity/dissimilarity of facial images. In essence, this represents a rather different data type from conventional biometric prediction, and so we do not provide here a more detailed survey of the extensive literature of facial expression analysis. [10] provides a recent survey regarding facial expressions.

- Voice: Voice is a modality through which individuals commonly, and involuntarily, often express emotions, and studies are reported in [150, 36] which focus on this behavioural trait. [124] describes a framework for emotion classification using a paradigm based on "emotion profiles". This approach, instead of assigning a more conventional single hard emotion label, interprets human emotion expression by providing multiple probabilistic class labels. Using this approach, the authors managed to capture the general emotional label at an accuracy of 68%.

Returning to keyboard-based prediction as an example raises some further interesting but more detailed issues. In the work reported in [43], for example, the experimenters adopted a 5-point Likert scale [104] for emotion labelling and used background key event collection software to record the keyboard data collected. However, the study included only 12 participants in the experimental database. The experiment did show encouraging results, suggesting around a 77% predictive accuracy for recognising emotions including confidence, hesitancy, nervousness, relaxation, sadness and tiredness, but the limitations of the database size obviously make strong or definitive conclusions difficult. In [112], key event collection software was employed, and a similar, but this time

11-point scale, adopted for emotion labelling. Using a somewhat larger database of 24 participants, this study reported an achieved recognition rate of around 75% for predicting cognitive stress.

Taking a rather less standard approach, [112] introduces a pressure sensing keyboard and records the key events and pressure sequences. The data are labelled according to emotional state by assuming that each emotion of interest is automatically linked to and generated by the specific task content presented to the participants, which may be seen as an area of weakness which requires further justification. This study, however, managed to collect data from a larger sample of 50 participants and generated an error rate of around 14% for ”happiness” and ”sadness” prediction.

In [112], the authors not only record the pressure sequence and key events but also record information about the mouse movements during interaction. This experiment produced a database which consisted of 24 participants. Emotional state is determined by the use of an emotional state questionnaire at the end of each task based on a 7-point Likert scale. This study reports, *inter alia*, that around 83% of participants showed increased physical keyboard pressure when put under stress.

Another key aspect here (and already noted in some cases above) concerns the size of databases used in reported studies, which has wide implications (we return to this later). Table 3 summarises the common databases available, for example, for the keystroke modality when used in the prediction of higher level states, and it is seen that only recently has a database become available which contains at least 100 subjects [53]. This work undertook a large scale data collection exercise which covered a variety of tasks, different activity scenarios (for example, both fixed, defined content-based tasks and free expression tasks) and involved 100 subjects providing common data in both keystroke and handwriting modalities.

Table 3. *Largest databases available (as noted in the literature) for emotion analysis*

Ref.	Capture method	Users	Emotion state questionnaire
[43]	Background key event	12	5-point Likert scale
[174]	Key event	24	11-point Likert scale
[112]	Key event and pressure sequence	50	Content determined emotion
[78]	Key event, pressure sequence and mouse	24	7-point Likert scale
[52]	Key event	100	10-point Likert scale

The idea of using biometrics-based prediction to assess mental states has found potential application in a variety of task areas. In [94], the author aims to introduce an eCommerce system that is aware of the user emotion via a combination of speech, facial image, motor functioning and body gesture. [85] uses an intelligent mouse-based system to monitor students' emotional state, while in [123], the authors propose a combination of keystroke and mouse dynamics to estimate affective state and communication preference in a given workspace in order to improve worker efficiency. In [76], the authors use a mobile phone platform to detect user emotion via data acquired from the user's social media applications. In [53], the proposed technique uses keystroke dynamics to detect a student's mental state, and [47] suggests some important potential for predictive biometrics in healthcare applications.

Over the past three years or so, higher level state prediction has also been investigated with various types of data collected from music [182, 183, 100], video [62, 15] and EEG signals [4, 180]. Despite the increasing interest in new modalities such as the EEG, most work in this area has concerned predictive medical applications [126, 95], although a study on improving driving safety by predicting emotion from EGG signals can be found [52].

3. Discussion and analysis

We now turn to some analysis of the selective overview presented above, a discussion of how this can help us to draw constructive conclusions about the applicability of predictive biometrics, and how best to support the development of this area of research in the future. Thus, we use the review above to offer some new and perhaps more focused insights into the field and its potential for future development.

3.1. Applicability of predictive techniques

We first consider the diversity of potential applications for biometrics-based prediction. There is a growing use of image processing and information about body data from pregnant women which focuses on gestational age estimation [57, 81, 179, 152]. This is also an approach which has been utilised in medical applications concerned with depressed patients [166]. This study has examined the changes in emotional processing by using a "face emotion recognition paradigm" to determine which treatment works most effectively. Indeed medical applications are frequently the target application domain for this type of work. [33] focuses on handwriting segments from patients with Parkinson's disease, and discusses how handwriting can be used to evaluate patients to determine how their handwriting patterns differ from those of healthy participants. The study found that patients with Parkinson's disease are less able to anticipate future movements in their writing execution. Following the same trend, [130] investigates the biomedical potential for using handwritten signatures to determine medical information relating to the effects of stroke.

The HCI area is also of considerable interest in the context of this topic. [116] reports experiments designed to test the efficacy of physiological measures to evaluate user experiences, while [86] predicts degree of subject frustration to help and support learners during the learning process, and [117] assesses users' emotional state during computer game play. [79] reports a process to develop an understanding of a subject's physiological status and predict stress, and [63] uses a variety of physiological signals to predict emotion, where body physiological characteristics such as cardiac function, temperature, muscle electrical activity, respiration, skin conductance and electrical activity of the brain are collected. The study reported in [173] detects both cognitive and physical stress by monitoring keystroke, and [7] presents a new approach to assessing emotional experience from users during computer-based interaction, using software which collects physiological measurements including heart rate, sweating (skin conductivity), muscle tension, and respiration rates.

Affective gaming [156] detects the force of button-pressing on a gamepad and uses this pressure data to measure and predict the affective state of the players, and [55] utilises a mobile phone touch screen to capture screen touch data to monitor a players emotional state. [47] examines the potential for biomedical applications of emotion prediction from keystroke.

3.2. Observations on methodological and procedural issues

It is clear that there is much to be gained if we can develop effective strategies and techniques which allow us reliably to predict conventional soft biometric properties from biometric data, and this is even more widely applicable if higher mental states can also be determined. This is especially the case as we see the collection of biometric information become increasingly widespread and routine.

It is equally clear that research to date in this potentially important area is relatively limited and is not always approached in ways which are likely to maximise effectiveness. In particular, the work formally reported can appear to be rather more fragmented than in the ”mainstream” of biometrics research, and this suggests there is scope for significant fundamental work still to be done.

What our review also reveals is the imbalance in the adoption of different biometric modalities for predictive purposes. The face modality is the most widespread modality adopted as a basis for this type of work, and there are good reasons for this. However, other modalities must surely have an important role to play, especially if we consider some of the most obvious areas of application (forensics, for example, where investigators may have little choice in determining the availability of particular evidential sources/modalities). For example, handwriting (in particular, the handwritten signature) is likely to grow again in importance with the current rise in the significance and widespread deployment of mobile biometrics and hand-held communication platforms.

Considering fundamental methodological issues further, it is apparent that there are inconsistencies about how acquired data samples are organised and, in particular, about the distribution of training/test samples. In our own work, we have tried to avoid the occurrence of different samples from the same individual occurring in both training and test sets, to avoid the risk of misleading results where individual identity might dominate the emotion prediction function. This appears not universally to be the case, however, and thus the interpretation and comparison of reported results can sometimes be difficult or uncertain.

Another particularly striking fact is that much of the work encountered reports experimental results based on extremely small sample sizes, again undermining the generality of conclusions which can be drawn, and limiting the extent to which the effectiveness of proposed techniques can be guaranteed. This, in general, is primarily a problem of the availability of appropriate or adequate databases, and we will return to this issue below.

From these general issues of process and methodology, we now move to some more specific lower-level analysis of the selective review undertaken, particularly with a view to providing some practical guidelines to inform and support future research.

4. Future development of predictive biometrics

It is important in the present context to note that our review points to some very specific messages about how best to support the development of this area of work in the future, and we see the identification of these lessons learned as a principal contribution of this paper. We therefore suggest the following issues as priorities for future research effort to maintain and extend the progress already summarised in our review.

4.1. Databases

In common with almost all major topics within the biometrics field, the availability of good databases is a key factor here in ensuring progress. While some extensive databases can be found, these tend to be related to a small number of modalities, and generally support a small range of predictive opportunities. For example, predicting gender from facial images benefits from the inherent nature of the metadata required and the fact that such data are generally well-labelled in relation to basic characteristics of interest.

If we move to, say, iris data, however, the situation is considerably less favourable, and once we consider the so-called ”higher level states”, databases are both more rarely encountered at all, are generally more limited in size when they are available and, indeed, are considerably more difficult to compile in the first place, both in terms of required resources (not just because of financial implications but also the human effort required) and in terms of the basic methodologies for assigning metadata labels. More attention to database requirements and greater effort in establishing large and publicly-available databases to support the development and evaluation of predictive techniques is essential for significant future progress in this field.

4.2. Ground truth determination

It is self-evident that a prerequisite for the evaluation of predictive algorithms is the availability of samples which are reliably and appropriately tagged with an accurate ground truth label. This raises two different but related issues.

While some properties which can usefully be predicted are generally (relatively) straightforward to label in a majority of cases (the gender of individuals, for example), others are less easy to label unambiguously or with a high degree of precision. Let us consider two illustrative examples.

First, let us consider the question of predicting subject age. While there can be little doubt for any specific individual of what an age label means, it is less clear exactly how we should use such very specific and naturally continuous rather than quanitised information (indeed, the general issue of how ageing affects biometric data processing is in itself a very challenging area [44]). For example, age is a continuous dynamic variable, and it would be difficult setting out to predict subject age to a very high degree of precision and granularity. It is much more common, therefore, to identify ”age bands” as the basis of prediction, but this leads to questions about what age bands are most appropriately adopted, how many bands should be considered, how to deal with the boundaries between bands, and so on. While some work has been reported to address this difficult question ([50], for example), this is inevitably a difficult area in practice, and one where standardisation of approach is currently hard to guarantee.

Second, we can see that the problems multiply significantly when we move away from relatively clear-cut characteristics such as age, gender and so on, to less easily defined characteristics such as higher level and emotional states. It is difficult enough simply to define a concept such as ”happiness”, without attempting to quantify an index of ”degree of happiness” with any confidence. We have seen various attempts to generate appropriate ground truth labels in these circumstances (making assumptions using task-based criteria, for instance, self-assessment, and so on [51]), but there is no doubt that this is a fundamentally difficult area which is yet to be addressed adequately in the biometrics literature.

4.3. Task definition and feature analysis

Many predictive tasks involve some specific activity or targeted response on the part of the test individual, and it is unsurprising that predicting emotional state is likely to be significantly task-dependent. It is apparent that there are no agreed guidelines about how to define experimental tasks as an objective basis for making meaningful comparisons across studies or in order to optimise predictive power for any given characteristic of interest, yet we can see that predictive performance can vary considerably depending on data generation conditions. Similarly, the basis of prediction requires the definition of features to extract from the samples collected in a predictive task.

Further work is required to understand better how to choose an optimal feature set which, again, is likely to vary depending on data collection conditions. Moreover, there is important work to be done in understanding the relationship between effective predictive features and the physiological and (perhaps more importantly) the behavioural mediators of measured performance arising in any particular task. These are areas which have received little attention in the literature to date, and which again suggest that the scope of general experimentation and analysis needs to be broadened.

4.4. Optimising processing infrastructure

It is very clear (and not at all surprising) that attainable performance will depend on the match between the data samples available, the statistical distributions they imply and the underlying processing infrastructure adopted for the prediction operation. While it is difficult to see how a formal optimisation strategy might be formulated and deployed, our review has suggested some particular directions in which implementation might be encouraged in order to exploit to best effect the predictive capabilities embedded in biometric data. Flexibility and adaptability are important issues here (the idea of more ”intelligent” and flexible data processing appears beneficial, for example [3, 1]), while questions of feature selection and classifier optimisation have been very little considered to date.

4.5. Complementarity in modality selection

While in conventional biometrics, where predicting personal identity from physiological/behavioural measurements is the principal aim, it has long been recognised that there is a value in combining identity evidence from multiple biometric modalities [146], this type of strategy seems rarely to be encountered in prediction tasks where the predictive target is a soft biometric characteristic. Although this may be largely a result of the lack of databases which provide the necessary data on which to develop practical techniques, it is nevertheless surprising, and suggests a strand of work which could pay dividends in the future. We know also that predicting higher level states (stress, for example) can be effectively achieved by measuring simple physiological indicators (sweating, heart rate patterns, etc.), and there appears to be scope for developing techniques which combine such simple measures with more subtle biometric measurements. These might combine different sources of physiological data, or might merge physiological and behavioural measurements in various ways.

4.6. Developing cross-disciplinary cooperation

The preceding discussion suggests very strongly that greater cooperation and collaboration which crosses traditional disciplinary boundaries is likely to provide a major impetus for this type of work. We have previously mentioned the growing cooperation between the biometrics and forensics communities [51, 189, 155], but the same principles can be more widely encouraged. Greater interaction between, *inter alia*, engineers and scientists, physiologists, neuroscientists and, perhaps especially, researchers and practitioners in the experimental psychology community, could pay real dividends in developing better methodologies to support the sort of work reviewed above. One example stands out here. We referred above to the importance of establishing reliable ground truth labels for data samples, and of understanding how different features might best reflect characteristics which we aim to predict, and it is in addressing issues such as these where crossing traditional disciplinary boundaries can potentially provide especially effective new momentum.

Thus, we see that our review of the field has not only assembled a valuable overview of current achievements and areas of on-going research, but has also led us to extract some important messages about areas where greater research effort might lubricate processes and initiatives currently in progress and, perhaps, stimulate a greater rate of progress in the future.

5. Conclusions

The field of biometrics is now well-established, and is supported by a wealth of research and development which has resulted in widespread deployment of biometrics in a variety of important practical applications. For obvious reasons the focus of this research has principally been the identification of individuals from acquired biometric data, or the checking of identity claims through a verification process based on such data. However, another dimension to more recent research in the biometrics field has been an interest in acquiring, analysing and utilising data which contributes to individual identity while falling short of unique identification capability, and such soft biometric information is increasingly been studied and exploited.

In this paper we have explored another, closely related, aspect of biometric data processing which derives from, and builds on, these more mainstream areas, focusing instead on how biometric data can be used to predict traits which characterise individuals. There is a growing literature reporting the prediction of **lower-level** characteristics such as age, gender and a variety of other defining features of individuals from biometric data, resulting in the extraction of valuable information short of identity itself which can contribute to many important practical applications, including security, forensics and healthcare, to take just the most obvious examples. It is interesting to note also that already it is possible to find examples of applications where conventional biometrics and what we have called here ”predictive biometrics” can be brought together to enhance conventional biometric processing [3, 2].

There is also a more recent interest in extending such predictive capabilities beyond these basic and most commonly considered properties to include **higher-level**, and perhaps more elusive, characteristics relating to emotional or mental states - such as degree of happiness, stress and other features characterizing individuals which have hitherto been less studied in the biometrics context but which can also contribute greatly to improving the range, reach and applicability of biometric processing.

However, research in this particular area represents a very small proportion of the totality of biometrics research, but in this paper we have examined the scope of this research and the diversity of approaches which can already be found. Perhaps more importantly, we have used this brief review of the field to identify and set out a number of issues which the available literature demonstrates to be imposing limitations on what can currently be achieved. This, it is suggested, can provide an initial roadmap to inform the development of a better understanding of some of the principal problems still to be fully explored, and can guide research towards solutions of maximum impact and reach in the future.

It is clear that the field of biometrics is already generating important and influential solutions in a variety of practical scenarios. This paper has addressed some of the areas which are broadening the range of application where further impact can be made, and has identified some techniques which, if developed appropriately, will contribute to this important process.

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